Efficient Brain Tumor Detection Approach using Hybrid Texture Feature Optimization and Machine Learning Algorithm

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Abstract

The early stage of brain tumor detection saves millions of lives worldwide. The variability of cell growth lowers the detection ratio of brain tumors. Recent research focuses on the texture property of MRI imaging and how to detect brain tumors at an early stage. For the purpose of detecting brain tumors, this paper suggests a hybrid texture feature optimization approach. Particle swarm optimization and genetic algorithms are two swarm intelligence methods that are combined in the MKSVM algorithm. The MKSVM algorithms classify the low-intensity features of texture and detect the area of brain tumor in MRI images. The extraction of texture features is an important phase of processing. In order to extract texture features, we apply discrete wavelet transform (DWT) methods. These methods are well known as texture feature extraction approaches instead of other transform methods. The BRATS dataset 2018 is used to test and evaluate the proposed technique using MATLAB software. Various existing algorithms, including CNN and DCNN, are used to compare the performance of the proposed method. The effectiveness findings indicate that the suggested method is more effective than current algorithms for brain tumor identification.

Keywords: - Brain Tumor, MRI Image, DWT, PSO, GA, SVM, CNN, DCNN

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Introduction

There are an extremely large number of cells that make up the human brain. Rapid, uncontrolled cell proliferation is thought to be a key factor in the development of brain tumours. Damage to healthy cells and disruption of brain function are consequences of unchecked cell growth[1,2]. Due to improvements in diagnostic imaging technology, the concept of automated brain tumour detection was presented. Rapid, unchecked cell proliferation is a hallmark of the current decade, yet accurate tumour identification is difficult due to tumours' diverse structures, varying sizes, and other variables. In most cases, investigators described brain tumour cells as both healthy and cancerous. The accuracy of brain tumour diagnosis remains a serious concern [3,4] despite the fact that several methods have been developed employing machine learning, deep learning, and hybrid techniques. Using a machine learning system for feature-based brain tumour detection is the primary emphasis of this research. Color, texture, and depth are all incorporated into the feature, which is a component of MRI scans. MRI pictures have no discernible colour or depth. MRI images are primarily characterised by their textural characteristics. There are several transform-based techniques used for extracting texture characteristics. The sequence of procedures based on MRI image blocks and coefficients. The techniques of the discrete wavelet transform are employed in this study for the extraction of texture features. The MRI pictures are discrete wavelet transformed layer by layer to reveal finer details and better approximations. [5]. High frequency bands include the information that makes MRI pictures so detailed, and they may be extracted directly from the image. Because of the approximate nature of the transform, feature processing time explosions are inevitable. Incorporating the collected features into a classification algorithm results in deformed performance due to noise that is both low in intensity and warped in kind. Several authors have recently implemented a swarm intelligence approach to optimise features. In this research, we suggested a hybrid approach to optimise features. The hybrid optimization strategy employs both particle swarm optimization and genetic algorithms. The measured value of Pbest is analogous to a genetic optimal solution[6], with the genetic algorithm serving as a local function in the optimization process. Gbest is the final step in processing global optimum features. The detection ratio in MRI scans is improved by their optimised characteristics. Classification algorithms are crucial in the detection of brain cancers. Classification is a process that involves all three types of learning—supervised, unsupervised, and reinforced. The majority of these works used a supervised learning approach using the classification method. Multiple methods, including those for binary classification and multiclass classification, are made available under the supervised learning umbrella. In this study, a binary classification strategy is adopted, and the Support Vector Machine method is reworked as a multi-kernel version. Support vector machines with multiple kernels can use more than two margin functions. Raising the number of support vectors improves the brain tumour detection rate. The remainder of the article follows the same section-based format that the second half did, this time in relation to brain tumours. In the third section, the proposed approach to brain tumours is outlined. The suggested algorithm's investigative analysis is discussed in Section IV. Our findings and recommendations for the future are presented in Section V..

II. Related Work

The diagnosis rate for brain tumours is rising because to the persistent efforts of several researchers. Optimization of features and integration of numerous machine learning algorithms have been used in recent works by a number of authors. When properly implemented, machine learning algorithms provide exceptional performance gains. This article details the most significant recent advancement in diagnosing brain tumours. The CNN model was suggested by Gajendra Raut and colleagues [2]. Before using deep learning, brain MRIs are improved to generate more data. Because of this, the labor-intensive process of diagnosing brain tumours may be completed more quickly with the help of automation. When applied to test data, the proposed model for detecting brain tumours obtains a 95.55% accuracy rate. Finding the tumour required employing convolutional neural network segmentation techniques. Using a novel systematic method supported by the DCNNA (Deep Convolution Neural Network Algorithm), Ramkumar and co. [4] define a number of 3X3 kernel sections. Brain tumour segmentation using DCNNA is validated using this approach, which is based on the BRATS dataset. Separating the complete cerebral venous system from MRI images is described as a unique, fully automated methodology by Zheshu Jia and colleagues [5]. This method relies on anatomical, morphological, and relaxation metre properties. Segmentation in the brain is particularly effective when the structure and surrounding tissue are very consistent. The ELM class of learning algorithms consists of one or more layers of hidden nodes. A Support Vector Machine strategy for Deep Convolution Neural Networks is suggested by Wentao Wu and coworkers [6]. (DCNN-F-SVM). The suggested method for dividing up brain tumours into manageable chunks may be summarised in three basic stages. First, the mapped data from image space to tumour marker space is understood by a Deep Convolution Neural Network. In the second stage, when the Deep Convolution Neural Network has been trained, the test pictures and expected labels are sent into the Integrated Support Vector Machine Classifier. To keep up with the rising demand, a precise and efficient method of segmenting pictures of brain tumours is required. The suggested study by Sumit Tripathi and colleagues [7] proposes a completely autonomous deep learning approach to estimate the tumour area in brain Magnetic Resonance Images, as exact analysis of the tumour of brain the area is essential in analysis of patient behaviour. With the addition of Residual Connections and Parametric RELU Parametric, A Network may have a greater range of possible layer counts while still maintaining a healthy level of balance. Based on the majority voting system, Ginni Garg and coworkers [8] suggested a hybrid ensemble approach that uses Random Forest (RF), K-Nearest Neighbor, and Decision Tree (DT) (KNNRF-DT). Brain tumours are classified as either benign or malignant based on the size of the tumour. Because of their superior performance, deep learning methods need more time to execute and a bigger training dataset than standard classifiers. WU DENG is only one example of those who come to mind. There is a suggestion in [9] for a hierarchical system to categorise and rank different tumour kinds. A technique in this field has been proposed after years of investigation into a wide range of specialists. Effective deep learning techniques were used to develop a method for segmenting brain tumours. The Gabor transform was used to convert spatial pictures into those with numerous orientations, as described by V. Jeevanantham et al. [10]. The multi-orientation brain pictures are created by taking the noise-filtered images and using the Gabor transform method. The hybrid characteristics, which are a combination of statistical and textural traits, are then computed using this modified brain picture. These methodologies for tumour identification and diagnosis are put to the test by using brain images from the BRATS 2016 dataset. This method has a sensitivity of 97.47%, a specificity of 98.52%, and an accuracy of 98.82%). [11] This research used a machine learning technique to pinpoint tumours in FLAIR pictures of the brain (MRI). We utilised a de-fleshed and co-registered skull from our multi-modal brain imaging collection. The two most recent and helpful advances in brain tumour localization are (1) the ability to create the picture in texture form with the text on-map, and (2) the ability to collect characteristics from the super pixels, both of which are crucial to our proposed technique. According to Wenbo Zhang and colleagues [12], MRI plays a crucial role in the assessment of brain tumour diagnosis and treatment planning. However, it is quite time-consuming to manually segment the MRI picture. As deep learning has progressed, several automated segmentation methods have been developed, however most of them can only be applied to 2D pictures, limiting their usefulness. We developed the ME-Net model, evaluated it on the BraTS 2020 dataset, and found that it performed well. To wit: Shubhangi Nema and co. [13] Here, we introduce the residual cyclic unpaired encoder-decoder network, which combines the concepts of residual and mirroring. RescueNet uses unpaired adversarial training on an MRI of the brain to isolate the tumour, then the tumor's core and enhancement zones. In this study, we propose using the Rescue Net end-to-end network architecture for separating brain malignancies. The need for large-scale annotated MRI data of brain tumours is met by the proposal of an unpaired training approach. It is suggested in this study by Rajat Mehrotra and colleagues [14] to use Deep Learning algorithms, which are based on artificial intelligence, to classify different types of brain tumours using publicly accessible information. These data sets classify BTs as either benign or malignant. Differentiating between the two classes is accomplished in this study by use of a Pre-Trained Convolutional Neural Network architecture trained on data from the former. [16] Colleagues of An Hu In this paper, we describe a novel heuristic-based method for the detection of malignant brain tumours at an early stage. Feature extraction, tumour segmentation, and deep belief network classification are the three cornerstones of the proposed approach. This research suggests an algorithmic method for identifying brain tumours. In the first step, we improved the picture quality by using a preprocessing approach for noise reduction. Colleagues led by Raheleh Hashemzehi [18]. Using these pictures, they teach a novel hybrid paradigm that incorporates a convolutional neural network and a neural autoregressive distribution estimation (NADE) (CNN). We next put our model to the test using 3064 T1-weighted contrast-enhanced images of three distinct forms of brain tumours. This model shows impressive performance after being trained using the 6-fold cross-validation method and the Adam optimizer, achieving 95% accuracy in front of a modest number of imbalanced brain tumour classification datasets. It was Gokila Brindha and others (P. The majority of brain cancers are detected using MRI scans [19]. Magnetic resonance imaging scans provide details regarding the abnormal brain tissue development. The approach of trial and error was used to develop this model. The decision of how many layers and filters to include in a model may be made with the use of optimization methods. For an MRI-based automated diagnostic system, Prabhpreet Kaur and colleagues [20] use refined segmentation and classification methods. The proposed method employs machine learning calculations based on data from two distinct cancer kinds. Different classifiers using images of different tumour kinds, such oedema, decay, and gloom, should be employed to verify the execution accuracy of the proposed indicative framework. Our proposed robotization for tumour detection on MR images is shown to be effective through cross-validation. When it comes to segmenting images and detecting objects inside them, deep neural networks excel [22]. Our method aids in the improvement and fine-tuning of these tactics, allowing for better specificity, accuracy, analysis, and precision in the prediction of a patient's brain tumour, all of which are essential in the field of restorative medicine. [23] The proposed method was evaluated against state-of-the-art deep learning systems using the popular BRATS2015 dataset. Each input brain picture had the skull digitally removed using the proposed three-hold approach. In this work, we used a modified version of a previously recognised segmentation method for identifying aberrant regions in brain images. Starting with a seed point to locate the optimal ROI for every brain imaging is the primary challenge for the region-growing algorithm. Super-resolution fuzzy C-means was utilised with SR-FCM-CNN by Fatih Zyurt and colleagues [24] to diagnose brain tumours. By using Squeeze Net, one of the most cutting-edge CNN architectures, the suggested technique is able to extract and classify features from segmented tumour pictures with ELM. The proposed approach has been used to segment tumours and to classify tumours. A Deep Convolutional Neural Network-based multistate brain tumour segmentation and classification model is introduced by Dáz-Pernas, Francisco Javier[26]. When compared to prior work, our concept stands out in part because it processes input pictures at three spatial scales using independent paths. We evaluated it on a publicly accessible dataset of T1-weighted, contrast-enhanced MRI images. Elastic data transformation was utilised to expand the training dataset and guard against overfitting. In this research, Jakub Nalepa and colleagues [30] propose a completely automated, end-to-end strategy for DCE-MRI analysis of brain tumours. For the DCE-MRI study of patients with brain tumours, we presented a fully automated deep learning-powered method that is carefully validated against benchmarks (BraTS'17 for tumour segmentation and a test dataset made available by the Quantitative Imaging Society), needs no user intervention, and yields repeatable results (ECONIB). Key ECONIB phases have been confirmed using both benchmark and clinical LGG data. Statistical analysis was used to back up the results of the studies. To Arshia Rehman and her colleagues at work [32] Significant progress and success stories have been achieved in machine learning, such as Convolutional Neural Networks and computer-aided tumour detection systems. The reported study is a novel attempt to classify brain cancers by using transfer learning and deep CNN architectures. The work of Mathiyalagan, Gomathi, and Dhanasekaran Devaraj et al. Using a machine learning classification strategy, a computer-aided, fully automated solution for identifying and classifying glioma brain MRI was created. Once the noise has been eliminated from the picture, fuzzy logic is used to pinpoint where the edges are. The image of the brain is then improved using contrast adaptive local histogram equalisation. The features are calculated using a Gabor-transformed version of the improved brain picture. The computed features are optimised using a GA feature optimization technique, and the enhanced features are classified using an ANFIS classification approach, which separates the source brain MRI image into glioma and non-glioma brain images. In the end, the fuzzy C means method is used to segment the tumour zones from the glioma brain picture. Simulation findings demonstrate that the suggested works in this article reach optimum performance with state-of-the-art methodologies by comparing the segmented tumour areas in glioma brain pictures to manually tumour segmented brain images.

III. Proposed Methodology

The suggested technique for detecting brain tumours is split into two parts: the first explains how to extract texture features and the second how to optimise hybrid features. Both parts use a multi-kernel support vector machine.

1. Texture Feature Extraction and optimization.

Discrete wavelet transform is very important methods in digital image processing and applied for the extraction of texture features. The processing of extraction applies as layer decomposition in DWT methods. the layer formation represents in form of high frequency (HF) and low frequency (LF). The further explosion of lower frequency explodes in high frequency (HF) and lower frequency (LF)[18,19]. The frequency of all components measured as mean function and standard deviation of lower frequency. The process of mean and standard deviation expressed as

The estimation of mean as

$$\mu = \frac{\sum_{i=1}^{N} Fi}{N} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(2).$$

The estimation of standard deviation as

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N}(Fi-\mu)^2}{N}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

The extracted texture features mapped in hybrid optimization algorithm. the hybrid optimization algorithm processes the features as map function. hybrid optimization algorithm is estimate optimal weight vector of texture features. Now the fitness function is formulated of the objective function that is $f(x) = \frac{1}{u}$. The processing of generation function defined as

$$xi + 1 = \mu xi(1 - xi) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(3)$$

Here x is a random number between intervals [0,1] and $\mu \in [0,4]$ is constant.

In order to solve the global optimization issue that arises during particle swarm optimization (PSO) processing in cognitive radio networks, it is necessary to employ a genetic algorithm to regulate PSO iterations and reduce their inadequacies. Particle location may be thought of as genetic information, and genetic production can be seen as fitness limitations. The current hybrid optimization selection procedure is described as[32,33].

$$\begin{cases} \Pr(Xi) = \dfrac{g(xi)X \exp(-h(xi))}{\sum_{j=1}^{N}(g(xj)X \exp(-h(xj)}\\ g(Xi) = \dfrac{1}{\exp(-SNRi)} \\ h(Xi) = \dfrac{1}{m}\sum_{j=1}^{N}|g(xi) - g(xj)| \end{cases} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(4)$$

Here g(Xi) and h(Xi) represent the degree of odder level

The subgroup of particle colon convergence population defined as

$$Var\{Ui\} = \frac{1}{N}\sum_{i=1}^{N}(fi(t) - f'(t)) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(5)$$

Now define the mutation operator for average fitness constraints function of particles

$$X_i^* = xi + cE(0,1) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(6)$$

Where c denotes the length of mutation and E(0,1) is mutation operator

After the mutation estimates the similarity of particles

$$sim(Xi, Xj) = 1 - \frac{|\ |Xi - Xj|\ |}{MaxXi, Xj \in Xc\{|Xi - xj|\}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots(7)$$

After the similarity estimation of particle finally assign the weight to available texture features.

2. Multi-kernel support vector machine

The multi-kernel support vector machine (MKSVM) is applied according to our data variants, it's also called dependable support vector machine.Consider the following classification problem. Suppose that sample in class +1 are denoted by a matrix $X1 \in R^{m1\times k}$ where Jth row $X \in R^k$ define data sample as similar, the matrix $X2 \in R^{m2\times k}$ show data point of class -1.

MKSVM define the hyperplane

$$\begin{cases} f_1(x) = W_1^T x + b_1 \\ f_2(x) = W_2^T x + b_2 \\ fn(x) = W_n^T + bn \end{cases}$$

In the nonlinear separable case, kernel MKSVM

$$\begin{cases} K(x, X)u^{(1)} + b^{(1)} = 0 \\ K(x, X)u^{(2)} + b^{(2)} = 0 \end{cases}$$

Where $X = [X_1^T X_2^T]^T$ and $K(\cdot)$ is an appropriately chosen kernel. The nonlinear classifiers are obtained by solving the following two optimization problems:

$$\begin{cases} \min_{u^{(1)}b^{(1)}\xi_2} \frac{1}{2} C_3\left(\|u^{(1)}.\|^2 + \left(b^{(1)}\right)^2\right) + \left(\frac{1}{2}\right)\left\|K(X_1,X)u^{(1)} + e_1 b^{(1)}\right\|^2 + c_1 e_2^T \xi_2 \\ s.t._{-(K(X_2,X)u^{(1)}+e_1 b_1)+\xi_2 \geq e_2;\quad \xi_2 \geq 0} \end{cases}$$

$$\begin{cases} \min_{u^{(2)}b^{(2)}\xi_1} \frac{1}{2} C_4\left(\|u^{(2)}.\|^2 + \left(b^{(2)}\right)^2\right) + \left(\frac{1}{2}\right)\left\|K(X_2,X)u^{(2)} + e_2 b^{(2)}\right\|^2 + c_2 e_1^T \xi_1 \\ s.t._{(K(X_1,X)u^{(2)}+e_1 b_2)+\xi_1 \geq e_1;\quad \xi_1 \geq 0} \end{cases}$$

Where $c_1, c_2, c_3$and c_4c are the positive penalty factors given by users, e_1 and e_2 are the vectors of ones of appropriate dimensions, $\xi_1$and $\xi_2$are the nonnegative slack variables, respectively.

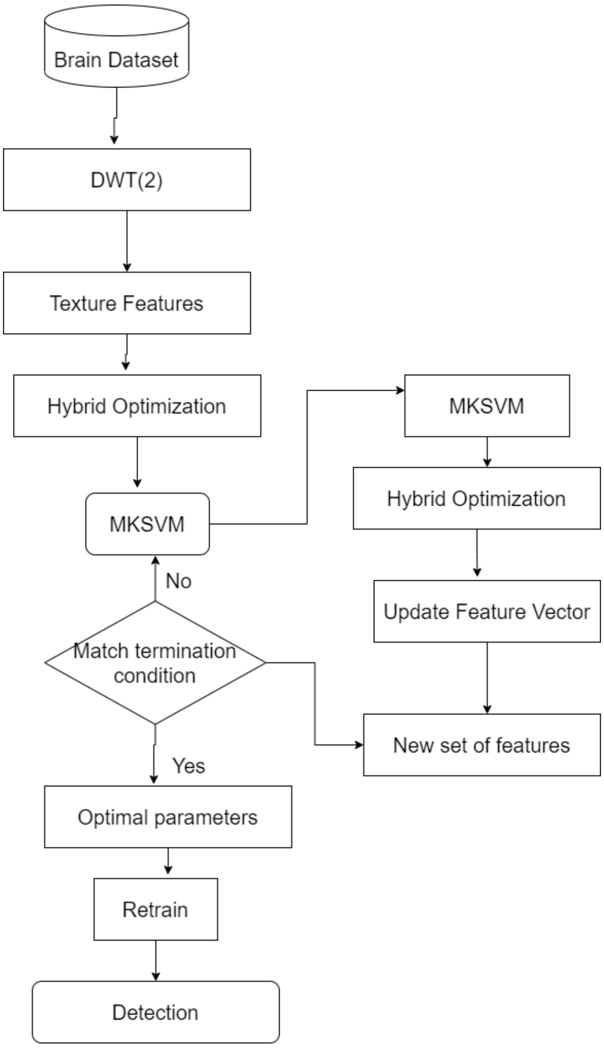

Figure-1 Proposed Model of Brain Tumor Detection using MKSVM

IV. Experimental Analysis

To evaluate the performance of proposed algorithm and existing algorithms for brain tumor detection using MATLAB software and windows operating system. the validation of algorithms tested on BRATS dataset. The BRATS dataset is collection of various tumors and normal images of human brains.The performance of proposed algorithm measure in terms of accuracy, sensitivity and specificity[30,31,32,33].

- Sensitivity- Precision measures the proportion of predicted positives/negatives which are actually positive/negative. $Sensitivity = \frac{TP}{TP + FN} \times 100$
- Specificity -It is the proportion of actual positives/negatives which are predicted positive/negative. $Specificity = \frac{TN}{TN + FP} \times 100$
- Accuracy-It is the proportion of the total number of predictions that were correct or it is the percentage of correctly classified instances. $Accuracy = \frac{TP+TN}{TP+TN+FN+FP}$

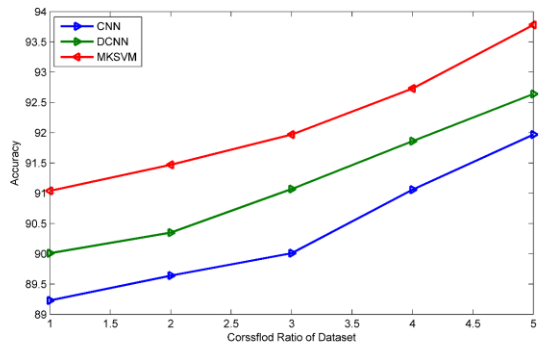

Figure 2 performance of accuracy of proposed algorithm with CNN and DCNN using corssflod ratio of dataset.

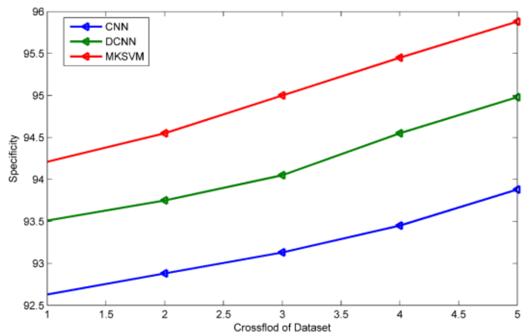

Figure 3 performance of specificity of proposed algorithm with CNN and DCNN using corssflod ratio of dataset.

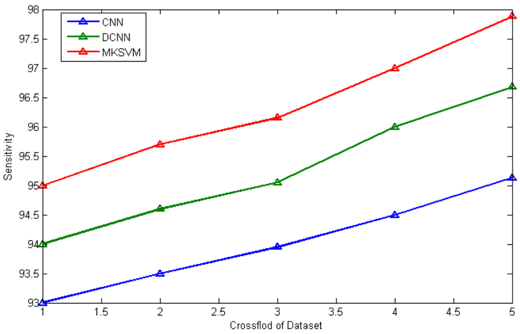

Figure 4 performance of sensitivity of proposed algorithm with CNN and DCNN using corssflod ratio of dataset.

V. Conclusion & Future Scope

The purpose of this research is to improve the rate at which brain cancers are detected. In this research, we present a multi-kernel support vector machine approach for brain tumour detection and classification. To improve vector machines' robustness, the multi-kernel function combines several non-linear operations into a single one. Support vector machines, with their ever-increasing margin, improve the detection rate of brain cancers. To extract texture features, discrete wavelet transform techniques are more helpful. The detected significance of the retrieved traits is high. Hybrid feature optimization works to improve the texture's more subtle and warped characteristics. Blending particle swarm optimization with GAs, we get hybrid feature optimization. When it comes to BRTAS data sets, the noise level is nearly cut in half by the hybrid optimization. These suggested algorithms for identifying and diagnosing cancers are tested on the brain tumours from the BRATS 2018 dataset. This method has a sensitivity of 92.47%, a specificity of 91.52%, and an accuracy of 90.82%. In a study of the classification rate for the proposed tumour diagnosis method, 92.4% was achieved over a range of mild to severe instances. Modern MRI scans of the brain will utilise deep learning algorithms to identify regions associated with cancer and strokes.

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